

## Kochi University of Technology Academic Resource Repository

---

|               |   |
|---------------|---|
| Title         | A WiFi-based Adjustment Algorithm for GPS Positioning on Smartphone           |
| Author(s)     | LI, Shuyang, AN, Xuehui   |
| Citation      | Society for Social Management Systems Internet Journal                        |
| Date of issue | 2011-09   |
| URL           | <a href="http://hdl.handle.net/10173/809">http://hdl.handle.net/10173/809</a> |
| Rights        |   |
| Text version  | publisher   |



Kochi, JAPAN

<http://kutarr.lib.kochi-tech.ac.jp/dspace/>

# A WiFi-based Adjustment Algorithm for GPS Positioning on Smartphones

Shuyang LI<sup>1</sup>, Xuehui AN<sup>1</sup>

<sup>1</sup> Department of Hydraulic Engineering, Tsinghua University, Beijing 100084, China

**ABSTRACT:** There are many advantages for outdoor augmented reality (AR) applying into construction management. Recently, smart phones equipped with GPS receivers and orientation sensors are more and more popular and they might make it easier to use the AR technology during construction process. But using commodity phones as devices has some challenges, such as the limited accuracy of GPS data, which is an important problem in outdoor AR application. A smart phone can be used to send and receive WiFi signal, which means the smart phone itself could be an access point and it could help to adjust GPS distance. In this paper, we present a two-step algorithm based on WiFi received signal strength (RSS) to adjust GPS distance. In the first step, the GPS data not meeting required accuracy standards are found and the smart phone with accurate GPS data become a new access point. Specifically, the distances ( $d_{GPS}$ ) between an access point and a smart phone using GPS coordinate data are calculated first. The RSS values ( $P_{GPS}$ ) corresponding to  $d_{GPS}$  are then estimated using the theoretical relationship between RSS and distance. The values of  $P_{GPS}$  and the series of real RSS values ( $RSS_{WiFi}$ ) between an access point and a smart phone are then compared using hypothesis test and the smart phones with inaccurate GPS distances are found. In the second step, the positions of inaccurate smart phones are adjusted using the data of  $RSS_{WiFi}$  and WiFi-based position estimation method. Then an iterative process of these two steps is performed to improve the accuracy of GPS positions. This algorithm is validated by field experiments first and studied further by computer simulation.

**KEYWORDS:** GPS positioning, received signal strength (RSS), smart phones

## 1. Introduction

In recent years, smart phones equipped with GPS and WLAN have been more and more commonly used around the world. These phones are more and more used as platforms for running outdoor augmented reality (AR) applications. Outdoor AR is a simple and efficient solution for modeling and visualization during construction process<sup>[1]</sup>. Due to the portability and easy availability of smart phones, it is very practically significant to develop AR applications for construction on smart phones.

Although many simple outdoor AR applications exist on smart phones, there are still problems in utilizing this AR technology for complex, large-scale and precision projects. The accuracy of positioning is one of the most important problems.<sup>[1, 2]</sup> In most cases, Global Position System (GPS) is used to estimate the position in outdoor AR applications. However, since the GPS signal is sensitive to the weather and may be interfered by obstructions, the feasibility of GPS positioning may be very low<sup>[1, 3]</sup>. To solve this problem, methods for adjusting GPS positioning were proposed by Yeh in 2009

and 2010. The methods are combining GPS and WiFi positioning results with different weights<sup>[3, 4]</sup>. In bad conditions for GPS, the combining positioning system using GPS and WiFi can reduce the positioning error efficiently. But in good conditions for GPS, the combining positioning system may increase the positioning error. And the weights selected in combining positioning method depend on human judgment and lots of off-line training. So it is not very flexible and practical. This paper proposes a practical two-step algorithm to adjust GPS positioning using WiFi signal.

The remainder of this paper is organized as follows: Section 2 gives a brief introduction on WiFi positioning; Section 3 presents solutions to pick up inaccurate GPS positioning results and adjust them; Section 4 evaluates the benefit of the solutions by simulating a positioning process; and Section 5 makes some concluding remarks.

## 2. RSS Positioning

There are many signal parameters can be used in a wireless network<sup>[5]</sup>, like using the signal's time-of-arrival (TOA), angle-of-arrival (AOA), time-difference-

of-arrival (TDOA), and (received signal strength) RSS. This paper focus on the positioning method using WiFi RSS.

## 2.1. Fading Model

A signal traveling from an access point to a sensor rapidly decreases as the transmission distance increasing. A log-normal fading path-loss model<sup>[6]</sup> is used to describe the relationship between RSS and the transmission distance. The model takes the form as:

$$P(d) = P_0 - 10nlg\left(\frac{d}{d_0}\right) + \sigma_{sh} \quad (1)$$

where  $P(d)$  is the RSS measured at the sensor,  $P_0$  is the transmission power measured at a reference distance  $d_0$  from the access point (the value of  $d_0$  is usually 1m),  $n$  is the path-loss exponent of the environment and  $\sigma_{sh}$  is the standard deviation of the shadowing noise. In an error-free case, the distance between an access point and a sensor can be uniquely determined by ignoring the  $\sigma_{sh}$  in equation (1), then log-normal model can be expressed as:

$$P(d) = P_0 - 10nlg\left(\frac{d}{d_0}\right) \quad (2)$$

Since the power received at a point is not a constant value but a series of data. The mean value of RSS series is often used as  $P(d)$  in practice. The parameters  $n$  and  $P_0$  can be fitted out by experiments.

## 2.2. Statistical Techniques for Position Estimation

Depending on the presence of training data, there are two types of position estimation techniques<sup>[5]</sup>: one is the mapping (fingerprinting) technique and the other is the geometric and statistical technique.

The purpose of this paper is to develop a portability method to adjust GPS positioning result with WiFi. Therefore, the database-free technique (statistical technique) is chosen as the approach for position estimation in a wireless network. In the statistical approach, formulating the theoretical framework by the following model

$$P_i(x, y) = P_0 - 10nlg(d_i(x, y)) \quad (3)$$

where  $P_i$  is the theoretical RSS between the  $i$ th access point and the sensor,  $d_i$  is the distance between the  $i$ th access point and the sensor,  $(x, y)$  is the position of the

sensor,  $(x_i, y_i)$  is the position of the  $i$ th access point. The distance  $d_i$  is calculated as:

$$d_i(x, y) = \sqrt{(x - x_i)^2 + (y - y_i)^2} + \eta_i \quad (4)$$

where  $i = 1, \dots, N_m$ ,  $N_m$  is the number of access points whose signals can be received by the sensor,

With a group equation by (3) and (4), the sensor's position can be solved. In fact, this is a non-linear least squares problems. We can define the least-squares cost-function as:

$$F(x, y) = \sum_{i=1}^{N_m} (RSS_i - P_i)^2 \quad (5)$$

where  $i = 1, \dots, N_m$ ,  $RSS_i$  is the real RSS between the  $i$ th access point and the sensor,  $P_i$  is formed by equation (3). Solving the sensor's position  $(x, y)$  is the same process of minimizing  $F(x, y)$ , and several different method can do this, like Gauss-Newton (GN) or Levenberg-Marquardt (LM) Method<sup>[7]</sup>. This paper use LM Method to solve the sensor's position. Figure 1 shows an example of how to solve an sensor's position. The right plot shows that the four sensors located at the peaks of the  $F(x, y)$  values. LM Method finds the minimum point in this area, and this minimum point is considered as the sensor's position.

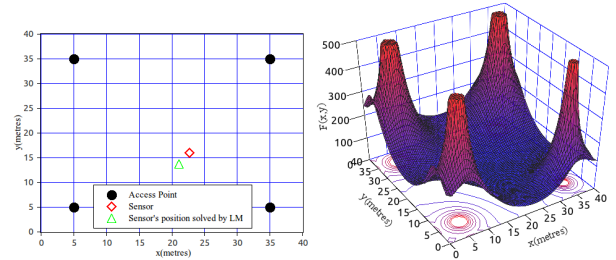


Figure 1: An example how the LM Method solves a sensor's position in a wireless network

## 3. Methods

The existing method of positioning using GPS and WiFi is estimating the position of a interest point using both GPS and WiFi, then combining these two result as<sup>[3, 4]</sup>

$$User(x, y) = \alpha GPS(x, y) + \beta WiFi(x, y) \quad (6)$$

where  $\alpha$  and  $\beta$  are the weights of GPS positioning result and WiFi positioning result, respectively. The weights

are related to weather conditions or the shading and they are selected from a pre-training scheme according to the judgment on weather and the user's location. This paper proposes a two step algorithm to improve the accuracy and flexibility of the weighting method. In the first step, find phones with the right GPS data using WiFi RSS by T-test method. According to the T-test results, if the accuracy of GPS data meets a certain criterion, the phone stops to receive WiFi signal and begins to transmit signal, which means turn itself to a new access point; and if the accuracy of GPS data is not accurate enough, adjust the position result using method in next step. Secondly, the phone's position is obtained combining WiFi positioning and GPS position with different weights, which are determined from the result in the first step.

### 3.1. Index of GPS Accuracy

Determining the accuracy of the GPS is an important problem of the existing weighting scheme method. When the GPS is inaccurate, combining GPS and WiFi positioning can decrease the positioning error, but when the GPS is accurate, on the contrary, the combining may increase the positioning error. This paper introduces an index to measure the accuracy of GPS using WiFi. As mentioned above the RSS between an access point and a sensor is a serial of data ( $RSS_{WiFi} = RSS_1, \dots, RSS_n$ ). The  $RSS_{WiFi}$  is proved to obey the normal distribution by experimental results<sup>[8]</sup>. Therefore, the power  $P(d)$  can be expressed as:

$$P(d) \sim \mathcal{N}(\overline{P(d)}, \sigma_{sh}^2) \quad (7)$$

where  $P(d)$  is calculated by equation (2),  $\sigma_{sh}$  increases with distance  $d$ . This statistical feature can be used to examine whether a transmission power is the mean value of the RSS serial. If a transmission power  $P$  is the mean value in a high-probability, then the distance  $d$  corresponds to  $P$  closes to the real distance in a high-probability. Since we want to examine whether  $P$  is the mean value and the standard deviation is not known, T-test can be used to do the hypothesis test<sup>[9]</sup>:

$$T \stackrel{\text{def}}{=} \left( \frac{\overline{RSS_{WiFi}} - P}{S/\sqrt{n}} \right) \sim t_{\alpha}(n-1) \quad (8)$$

where  $\overline{RSS_{WiFi}}$  is the mean value of a statistical sample ( $RSS_{WiFi}$ ) of RSS between the access point and the sensor,  $P$  is the value we want to examine whether is the mean value,  $n$  is the size of  $RSS_{WiFi}$ ,  $S$  is the

standard division of  $RSS_{WiFi}$ ,  $t_{\alpha}(n-1)$  presents the student distribution with a freedom  $n-1$ . If

$$\frac{|T|}{t_{\alpha/2}(n-1)} \leq 1 \quad (9)$$

then  $P$  is considered as the mean value of  $RSS_{WiFi}$ , otherwise the probability that  $P$  is the mean value is very small. This can be used to evaluate the accuracy of GPS. The detail process is: Firstly, calculate the distance  $d_{GPS}$  between the access point (whose position is known) and the sensor using GPS positioning result. Secondly, calculate  $P(d_{GPS})$  with equation (2). Finally, calculate an index  $e = \frac{|T|}{t_{\alpha/2}(n-1)}$  and use T-test to examine the accuracy of GPS positioning with equation (8).

In order to confirm whether this method works, field experiments and simulations are taken to check the effect of the GPS accuracy index.

#### 3.1.1. Experiments to Check the GPS Accuracy Index

Two android phones (MOTO Mileston 2 and MOTO Defy) were used to do the field experiments. One smart phone was used as an access point and another is used as a sensor. The distance between the two phones was changed from 1m to 100m. At the same time, the two phones received GPS signals. Distances between phones were calculated by GPS positioning results, and the RSS serial at those distances were recorded. Then the GPS accuracy index  $e$ , which was calculated by equation (9). The results is shown in Figure 2. The three largest GPS distance errors are found by the index.

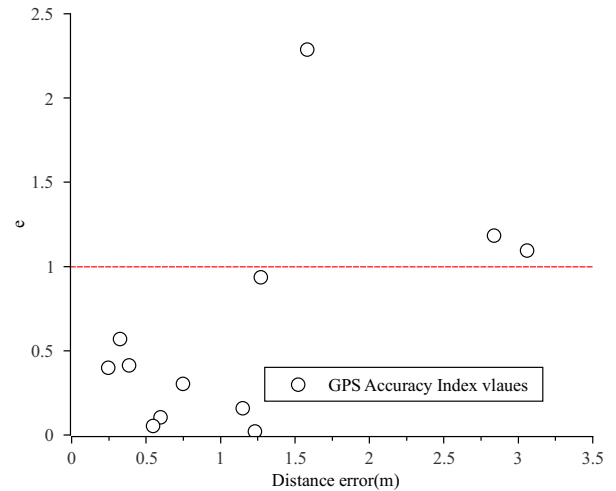


Figure 2: Using RSS serial and GPS distance between two smart phones to calculate the GPS accuracy index.

### 3.1.2. Simulations to Check the GPS Accuracy Index

For further study of the index, use SciLab to simulate a WiFi access point and a sensor. Assuming the parameters in equation (2) are  $P_0 = -45$ ,  $n = 2.0$ . Generate RSS serial between the access point and the sensor with equation (1) by using parameters  $P_0$ ,  $n$  and  $\sigma_{sh}$  related to distance. First of all, do times of simulations at different distances and fit  $P_0$  and  $n$ , as shown in Figure 3.

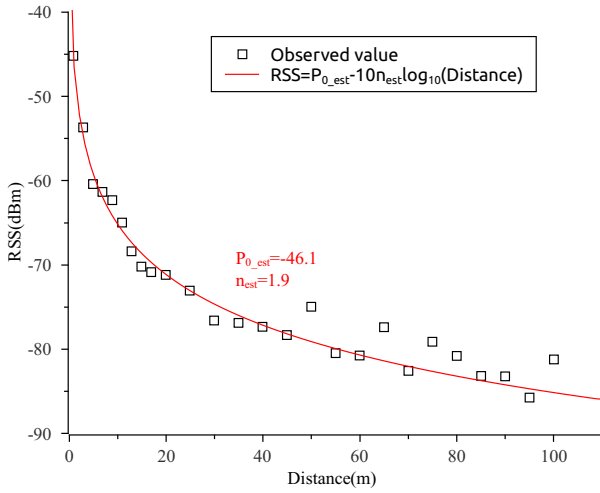


Figure 3: The plot of fitting for relationship between RSS and Distance.

Then change the distance between the access point and the sensor from 1m to 50m. At each distance, calculate  $e$  with equation (9) under different distance errors. For each distance under each error, 50 simulations are taken and a mean value is taken as the final index. The results are shown in Figure 4.

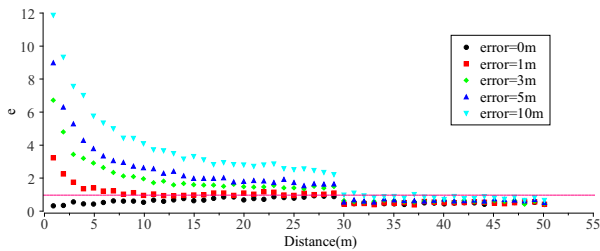


Figure 4: The performance of accuracy index under different distance errors.

Figure 4 tells us that the index  $e$  is all less than 1.0 when the measured distance is equal to the real one.

While the distance is smaller than 30m and the error is larger than 0,  $e$  is larger than 1.0. But while the distance is larger than 30m,  $e$  is almost always less than 1.0. That is because a larger distance leads to less sensitive changes of RSS and a larger standard division of RSS. Thereupon the index  $e$  is suitable for a distance smaller than 30m. Figure 4 also shows that  $e$  is too strict and too sensitive when the distance is small. To solve these problems, equation (9) is modified as:

$$e = \ln\left(\frac{|T|}{t_{\alpha/2}(n-1)} \times \frac{\overline{RSS_{WiFi}}}{P_0}\right) \times \frac{\overline{RSS_{WiFi}}}{P_{30}} \quad (10)$$

where  $P_{30}$  is calculated by:

$$P_{30} = P_0 - n \lg(30) \quad (11)$$

Do the simulations again using equation (10) instead of equation (9). The results are shown in Figure 5. The modified  $e$  mainly picks out the distance error larger than 5m.

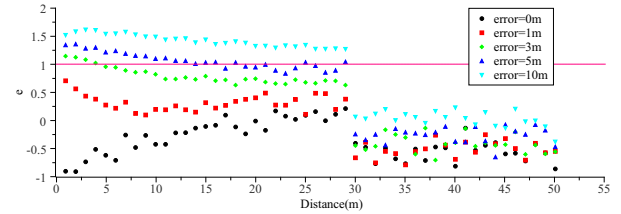


Figure 5: The performance of modified accuracy index under different distance errors.

## 3.2. Methods of Combining GPS and WiFi Positioning Results

Since the GPS accuracy index  $e$  is a kind of indicator which shows how accurate the GPS positioning is. It can be used to give the weights for combining GPS and WiFi positioning results. The weights in equation (6) are taken as:  $\alpha = \frac{1}{e}$  and  $\beta = 1 - \alpha$ .

## 3.3. Process of the Adjusting Algorithm

Figure 6 shows the flow chart of the two-step adjusting algorithm for GPS and WiFi positioning.

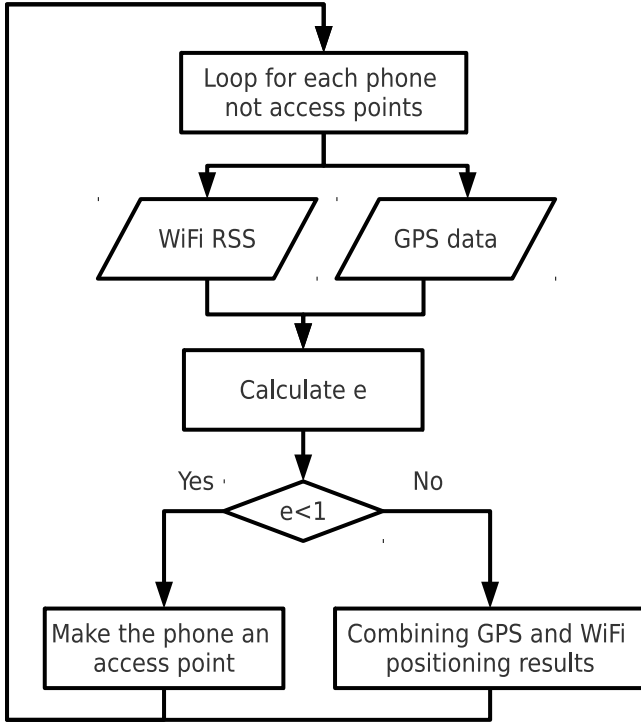


Figure 6: The process of the adjusting algorithm.

In practice, execute this algorithm in an iteration process. Then the accuracy of positioning can be improved step by step.

### 3.4. Outline of the WiFi Network and Users in Simulation

To check the performance of the adjusting algorithm, a positioning process is simulated. The outline of the network is shown in Figure 7.

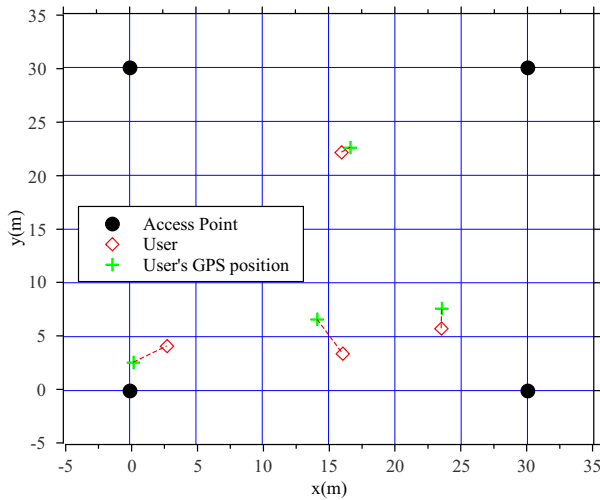


Figure 7: The outline of the network used in simulations.

The access points are set up at four corners of an  $30m \times 30m$  area. Inside this area, there are four users whose positions are generated randomly and their GPS positioning results are obtained using a normal distribution function. According to the parameters of the GPS's distribution, three cases are simulated as shown in Table 1. Case 1 represents the situation that the accuracy of GPS is very high; Case 2 represents the situation that the accuracy of GPS is very low; Case 3 represents the situation that the accuracy of GPS is dispersive. Case 4 represents the situation that only WiFi positioning is adopted.

| Case | Mean value of GPS errors | Standard division of GPS errors |
|------|--------------------------|---------------------------------|
| 1    | 2                        | 1                               |
| 2    | 18                       | 4                               |
| 3    | 10                       | 10                              |

Table 1: A list of parameters to simulate GPS positioning results.

## 4. Results

Each case in Table 1 is simulated for 50 times. And in each simulation the maximum number of iterations is 50. Figure 8 is the accumulation curves of the three cases. A comparison of the mean error between GPS positioning and the proposed method is listed in Table 2. And the mean error of Case 4 is 4.75m. These results indicate that in all the three cases, the proposed two-step algorithm can increase the accuracy of the positioning results. Even in the situation like case 3, the mean GPS positioning error is equal to 11.85m, the proposed method still can make the positioning result better than using either GPS positioning or WiFi positioning.

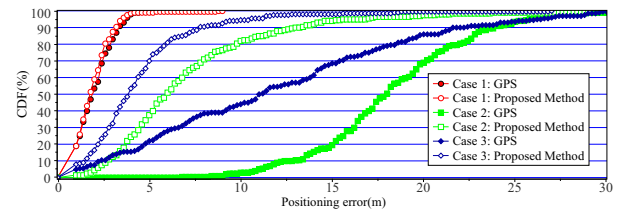


Figure 8: CDF of simulation cases.

| Case | Mean error<br>of GPS<br>positioning(m) | Mean error<br>of proposed<br>algorithm(m) |
|------|--|---|
| 1    | 1.95                                   | 1.86                                      |
| 2    | 18.19                                  | 7.10                                      |
| 3    | 11.85                                  | 4.48                                      |

Table 2: Mean errors of the two kind of positioning methods.

## 5. Conclusion

This paper presents a new method to adjust GPS positioning in a wireless network. The simulation results indicate that this algorithm can decrease the positioning error effectively. And compare to previous work, this algorithm does not depend on human judgments and is suitable to different situations.

This method is to be tested in more field experiments. And further studies can focus on the positioning adjusting method in the 3-Dimension space.

## References

- [1] A. H. Behzadan and V. R. Kamat, "Georeferenced registration of construction graphics in mobile outdoor augmented reality," *JOURNAL OF COMPUTING IN CIVIL ENGINEERING*, vol. 21, no. 4, pp. 247–258, 2007.
- [2] J. B. Gotow, K. Zienkiewicz, J. White, and D. C. Schmidt, "Addressing challenges with augmented reality applications on smartphones," in *Mobile Wireless Middleware, Operating Systems, and Applications* (O. Akan, P. Bellavista, J. Cao, F. Dressler, D. Ferrari, M. Gerla, H. Kobayashi, S. Palazzo, S. Sahni, X. S. Shen, M. Stan, J. Xiaohua, A. Zomaya, G. Coulson, Y. Cai, T. Magedanz, M. Li, J. Xia, and C. Giannelli, eds.), vol. 48 of *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, pp. 129–143, Springer Berlin Heidelberg, 2010.
- [3] S.-C. Yeh, W.-H. Hsu, M.-Y. Su, C.-H. Chen, and K.-H. Liu, "A study on outdoor positioning technology using gps and wifi networks," in *Proc. Int. Conf. Networking, Sensing and Control ICNSC '09*, pp. 597–601, 2009.
- [4] S.-C. Yeh, W.-H. Hsu, and Y.-S. Chiou, "Adaptive-weighting schemes for location-based services over heterogeneous wireless networks," in *Proc. IEEE 71st Vehicular Technology Conf. (VTC 2010-Spring)*, pp. 1–4, 2010.
- [5] S. Gezici, "A survey on wireless position estimation," *Wirel. Pers. Commun.*, vol. 44, pp. 263–282, February 2008.
- [6] R. A. Malaney, "Nuisance parameters and location accuracy in log-normal fading models," vol. 6, no. 3, pp. 937–947, 2007.
- [7] K. Madsen, H. Bruun, and O. Tingleff, "Methods for non-linear least squares problems," 1999.
- [8] Z. Jian, Z. Hai, S. Pei-gang, and B. Yuan-guo, "Equilateral triangle localization algorithm based on average rssi," *Journal of Northeastern University(Natural Science)*, vol. 8, 2007.
- [9] G. Yubo, *probability and statistics*. TSINGHUA UNIVERSITY PRESS, 2005.